Activity-based dynamic traffic modeling: Influence of population sampling fraction size on simulation error.
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Activity-based dynamic traffic modeling: influence of population sampling fraction size on simulation error

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Activity-based dynamic traffic modeling: influence of population sampling fraction size on simulation error

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Abstract
Activity-based models hold much promise for dynamic traffic modeling as they are able to predict travel demand on a high time resolution level. At the same time, however, the models use micro-simulation leading to simulation error in predictions which may become significant especially at the high temporal resolutions required by dynamic traffic models. In this paper, we address the question what the impacts of simulation error is for dynamic traffic modeling as a function of the size of the fraction of the population simulated (or number of runs of the model). Since activity-based models tend to allow a larger study area than a dynamic traffic model, we distinguish between an inner and outer study area and consider the differential impacts of sampling fraction sizes for the two areas. The activity-based model ALBATROSS is used to predict travel demands under varying conditions of size of the synthesized population. The results of an error-variance analysis indicate that the size of simulation error is substantial even when a 100% fraction of the local population is simulated. Furthermore, we find that for highways the reliability of predictions depends primarily on the size of the internal population, whereas the reliability for local roads responds more strongly to the size of the external population.

Keywords
Dynamic traffic modeling, activity-based modeling, micro-simulation, simulation error, sampling.

Preferred Citation
1. Introduction

Now that large-scale activity-based models of travel demand are becoming operational linking the models with dynamic traffic models is high on the research agenda (Hao et al. 2010). Dynamic traffic models require that travel demands are known for different time periods of the day with sufficient temporal resolution. Activity-based models are well adapted to this requirement as these models predict activity-travel patterns of individuals on a continuous time scale of a day or, at least, on a high level of temporal resolution. Hence, the linkage of activity-based models and dynamic traffic models is generally considered to be very promising (Lam and Yin 2001, Lin et al. 2009, Davidson et al. 2007). The integration of activity-based models and a dynamic traffic models has been demonstrated in several studies in the literature (Hao et al. 2010, Lin et al. 2010). However, an issue that requires attention is simulation error. In most instances, activity-based models use micro-simulation to generate activity-travel patterns of the individuals of a studied population (Arentze and Timmermans 2004, Roorda et al. 2008, Horni et al. 2010). Simulation error may become a significant factor especially at the high level of temporal resolution involved in dynamic traffic modeling.

Although several studies have considered the use of activity-based models for dynamic traffic modeling, little is known about the impact of simulation error on dynamic traffic prediction. Simulation error of activity-based models has received some attention in the literature. Castiglione et al. (2007) investigated simulation error of an activity-based model as a function of number of runs of the model, choice facet (mode, location, etc.) and geographic detail of predictions. They looked at the speed with which results converge toward a stable value. Veldhuisen et al. (2007) analyze the effects of simulation error in output of the RAMBLAS activity-based model. Cools et al. (2011) investigated the effects of simulation error as a function of ways of aggregation of predictions of the FEATHERS activity-based model – the Flanders, Belgium equivalent of Albatross – focusing especially on travel demand indicators such as number of trips and distance travelled. Rasouli et al. (2011) similarly describe results of an uncertainty analysis of the ALBATROSS model for a range of activity type, mode and timing segmentations of aggregated predictions of trip distance. Rasouli and Timmermans (2011) give a comprehensive review of work in this area. To the best of our knowledge a systematic analysis of simulation error of activity-based models on the level of dynamic traffic simulation does not exist.

In this study, we analyze the size of simulation error using the activity-based model ALBATROSS (Arentze and Timmermans 2004, Arentze et al. 2008a). Like in micro-simulation models in general, the generation of a synthetic population for simulation is a first step in this model. To reduce computation time, it is common practice to use a limited random fraction rather than a full population as the basis for prediction and rescale trip flows back to population level. Simulation error introduces random variation of predicted traffic flows on the road network and the smaller the sampling fraction the larger the scale of the error will be. Thus, our analysis focuses on investigating the size of simulation error in predictions of traffic flows (throughout a day) as a function of the size of the simulated population (sampling fraction). To measure the effect of sample size on the error, we conduct multiple runs of the Albatross model using different sampling fractions of the population. The results provide insights into the size of simulation error in the prediction of dynamic traffic flows for a representative activity-based model and a large-scale study area. Based on these
insights conclusions can be drawn regarding the required sample size of a population (or, reversely, number of model runs) in applications where the output of the activity-based model is to be used for dynamic traffic modeling.

In the remainder of the paper, we describe the approach and the results of the analysis. First, we will briefly review the current state of the art in the field of linking dynamic traffic models to activity-based models and explain how such a linkage was implemented in case of the ALBATROSS model to highlight some operational issues, such as study area delineation and border effects. Next, we will explain the proposed method to analyze simulation error, introduce the case study and discuss the results of the simulations and analyses of error. We conclude the paper with discussing the major conclusions and identifying remaining problems for future research.

2. Aim and approach

Where static traffic models consider a given moment in time (often a day or a part of a day), the aim of dynamic traffic modeling is to predict the flows of traffic on a road network from moment to moment in continuous time. There is not one single approach that has emerged from the work in the field of dynamic traffic modeling (Peeta and Ziliaskopoulos 2001). It is not our intention to review this field of research in any detail. It suffices here to give a characterization of the field in terms of some major classifications. A first way of classification distinguishes (dynamic) assignment and simulation models or, alternatively termed, equilibrium and non-equilibrium models (De Romph 1994, Bliemer 2001). Simulation models propagate the traffic flow along the routes across a road network through time; they do not model route choice explicitly. An important model type of this category assumes that traffic flows behave just as a fluid streaming through a network of channels and borrows its formulation from hydrodynamic theory in physics (Daganzo 1997). On the other hand, in assignment models route choice is an explicit step in the process. These models involve an iterative process of computing routes of trips and updating travel times given the distribution of traffic. Dynamics are introduced by adopting discrete time periods or continuous time functions in the models. It is noted that the existence of time variance by itself does not imply that a model is dynamic. Only if movement of vehicles is traced through time, that label is warranted.

A second dimension on which existing modeling approaches can be distinguished concerns the level of disaggregation of the behavior that is modeled. Macroscopic models consider traffic at an aggregate level of flows. Although they may consider some kind of segmentation of vehicle types, they do not consider behavior of vehicles on an individual level. The mentioned hydrodynamic models are traditionally the most widely used type of dynamic macroscopic model. On the other hand, microscopic models are vehicle-oriented models where the movement of individual vehicles is tracked with the ability of capturing the interactions between individual drivers. Microscopic properties such as the state of each vehicle (i.e., the position and the speed of a single vehicle) are represented by the models. Microscopic models usually have stochastic characteristics while macroscopic models are deterministic. Examples of large-scale systems that use microscopic traffic modeling are TRANSIMS and its successor MATSIM (Raney and Nagel 2005, Balmer et al. 2007). Finally, mesoscopic models take in a position somewhere in between these extremes and handle
packets of vehicles. Examples of mesoscopic models are CONTRAM (Leonard et al. 1978), DynaMIT (Ben-Akiva et al. 1998) and DYNASMART (Mahmassani et al. 1998).

Irrespective the modeling approach, a critical issue in the application of dynamic traffic models is availability of data about the timing of trips. Traditional trip-based travel demand models (most notably the four-step model) lack the temporal dimension to support dynamic traffic modeling. These models generate a trip matrix which represent a time period of a day or at best is broken down in a few parts of the day such as morning peak hours, evening peak hours and rest day. An approach that has been adopted to anyhow apply dynamic traffic models based on this is to assume for each OD relation some temporal distribution of the traffic flow. However, this is clearly an ad-hoc approach that is unsatisfactory from a point of view of behavioral modeling. It has been recognized that the activity-based approach provides a more satisfactory way to provide the needed timing information of trips (in the context of complete activity patterns) in addition to other attributes of trips.

Activity-based models predict travel demand as a derivative of the activities individuals wish to conduct in space and time. These models consider an entire day of an individual as unit of analysis and predict in an integrated fashion which activities are conducted, where (location), when (timing), for how long (duration), sometimes whith whom and, if traveling is involved, the transport mode used. Activity and travel episodes are predicted on a continuous time scale or, if done in a discrete way, a relatively high temporal resolution is assumed so that departure times of trips are known. A further basic assumption of the activity-based approach is that the household context is important for many activity-travel decisions, given that allocation of resources and joint activity participation are often in play on this level. The more advanced models also take these within-household interactions into account.

Activity-based modeling is generally based on micro-simulation. This means that activity-travel decisions are simulated on individual level. To create a synthetic population that is consistent with known characteristic of a true population, Iterative Proportional Fitting (IPF) is widely used since this method was introduced by Beckman et al. (1996). Synthesizing complete households is not a trivial task and various approaches have been proposed to achieve this. For example, the population synthesizer module of ALBATROSS uses so-called relation matrices to synthesize individuals and households simultaneously in an IPF procedure (Arentze et al. 2008b).

Given the microscopic approach, the output of an ABM consists of as many activity-travel patterns (schedules) as there are individuals in the synthetic population. These data can provide the necessary input for dynamic traffic modeling both in a microscopic and macroscopic way. Trips can be extracted from the activity schedules with data about origin, destination, transport mode and departure time (Rieser et al. 2008). To support a macroscopic approach, the trips can be aggregated into trip matrices for different times of day. As in static traffic assignment procedures, the trip matrices are based on some zoning system for the study area. Unlike the static case, however, the temporal dimension is much more refined by assuming a subdivision of a day in time slices of sufficient short duration (for example of an hour) to meet the requirements of dynamic traffic modeling.

As the above suggests, activity-based models matches well the data needs of dynamic traffic modeling. However, existing utility-based as well as rule-based models (ALBATROSS) are
stochastic to acknowledge unexplained variance in the various steps of the decision process. Monte-Carlo simulation is used to generate decisions. The simulation error that results may imply that predictions are not sufficiently reliable on the level of (dis-)aggregation on which the data is used. Usually, this is not problematic for static traffic modeling (Beckx et al. 2010). However, dynamic traffic modeling involves a higher degree of disaggregation along the temporal dimension of the trips. On this higher level of disaggregation it is not known a-priori whether simulation error leads to substantial margins of uncertainty around predictions of traffic flows. This is amplified by the fact that in dynamic models more so than in static models traffic systems tend to display non-linear behavior so that small changes in conditions (error) can have large effects.

In practice, simulation error on any given level of aggregation of model output can be controlled by choice of \( N \) where \( N = \text{population size} \times \text{number of runs of the model} \). Everything else equal, the larger the population or the larger the number of runs the smaller the expected simulation error will be and vice versa. Population size can be varied by synthesizing only a fraction (< 1) of the full population of a study area or, if the true population is small, a multiple (> 1). We are interested here in reliability of prediction of an activity-based model when the output is to be used for dynamic traffic modeling and consider the question what the reliability is for typical \( N \) and in what way this responds to variation in this parameter.

3. Method

In this section, we describe the method we used to investigate sampling error in case of dynamic traffic modeling. As an activity-based model we use ALBATROSS. Albatross predicts activity schedules of individuals on a continuous time scale and takes within household interactions regarding resource allocation and joint activities of household members into account (Angrainni et al. 2009). In terms of (dynamic) traffic modeling we assume a macroscopic model which takes trip matrices for small time intervals across the day as input. In this section, we describe the method used to generate the trip matrices, the study area considered and the set-up of the numerical experiment.

Generating time-dependent trip matrices

A trip matrix for a given time window represents all trips of which the departure time falls within that time window. It is straightforward to generate such trip matrices based on the output of an activity-based model provided that the latter predicts (activities and) trips on a continuous time scale. A trip matrix for a given time interval is obtained by counting for each OD pair (cell of the matrix) the trips in activity schedules that match that origin and destination and where the departure time falls within the specified time interval. Since in traffic modeling we are interested in the movements of vehicles (and more specifically cars) we must take into account that multiple persons may travel together in a single vehicle. The classification of transport mode used in Albatross –and many other travel demand models– distinguishes between traveling as car passenger and as car driver. By selecting only trips made as car driver the trip matrix will represent flows of vehicles.

Whereas the time dimension does not present any difficulty, a possible mismatch in size of study needs to be taken care of. Such a mismatch is likely to occur, since dynamic traffic
models, given the high computational demands of these models, often assume a smaller scale of the study area than activity-based models do (Jeihani et al. 2006). The model used for the present study indeed gives rise to such a difference. Albatross assumes the whole of The Netherlands (national scale) as study area whereas current dynamic traffic models operate on a smaller area. A trip matrix used for traffic modeling generally represents trips going into the area from outside and trips going out of the area from inside as external flows that enter (going in) and exit (going out) the road network at additional nodes that are added at the places where the network is cut off by the borders of the local study area. Even though the routes of such external trips may be responsive to traffic conditions, the size of external flows at entry and exit points is fixed in the traffic simulation. For the activity-based model which assumes the larger area this means that predicted trips that have a trip end (origin or destination or both) outside the local area should be assigned to the nodes where they enter or exit the smaller area.

In creating a synthetic population, it is possible to use different sampling fractions for the (local) study area and the outer area (rest of the Netherlands). As the people living outside the study area make up a large proportion of the total national population, stability of predictions of external flows can be achieved already with a relatively small sampling fraction of this part of the population. For this reason we differentiate and use a smaller sampling fraction for the external population than for the internal population. In generating the trip matrices, trips are weighted by the inverse of the sampling fraction used so that trips originating from individuals residing in the outer area will have a higher weight and, hence, the resulting trip matrix should represent traffic flows on the basis of the full population.

A further issue that deserves attention concerns the coverage of traffic segments by the model. Just as conventional trip-based models, activity-based models consider only passenger transport; freight transport is not represented in the trip matrix derived. To account for freight transport, trip flows predicted by Albatross are multiplied by factors that represent the proportions of freight transport in total traffic flows by time of day. In addition it should be noted that Albatross does not predict activity schedules of children in households or persons living outside a household context. However, the error of not including these groups will be small as they consist for the vast majority of individuals that have not yet reached the minimum age for driving a car. Finally, also international travel is not incorporated in the predictions.

The study area
The study area we consider for the analysis roughly coincides with the area of North-Holland, a province situated at the North Sea in the northwest part of the Netherlands as depicted in Figure 1. The major cities and towns of the province are Amsterdam, Haarlem, Hilversum, Den Helder, Alkmaar, Zandaam, and Hoorn. The island of Texel is also part of the province and of the study area. Amsterdam, which is the financial and cultural capital of the Netherlands, is located in North-Holland. Many large Dutch institutions have their headquarters there. Moreover, the city is a famous touristic destination drawing 4.2 million tourists every year. As the region is characterized as a city of finance and tourism, the Netherlands’s main airport, Amsterdam Airport Schiphol is located southwest of Amsterdam.

Trip matrices are generated assuming a zoning system that divides the study area into 436 zones. The zones are postcode areas which by and large coincide with neighborhoods.
Albatross uses the same zoning system for the Netherlands as a whole. On the level of Albatross the larger study area counts 3987 zones (postcode areas). Although the local study area is bordered for the most part by water (North Sea and IJsselmeer), external traffic flows are still substantial given the above regional functions of especially Amsterdam and the airport. The entry and exit points identified for the area are located in 25 postcode areas at the border of the area (see Figure 1). As for the temporal dimension, the day is subdivided in time intervals of one hour. However, for the night time a lower resolution is used. In sum, the following time intervals are assumed: 3 am – 6 am; 6 am – 8 am; 8 – 9 am; 9 – 10 am; …. 7 – 8 pm, 8 pm – 3 am. As a result the dimensions of the trip matrix include 15 time intervals and 436 + 25 origin and destination zones amounting to a total of 3,187,815 OD-by-time cells.

**Set-up of the experiment**

In order to see how dynamic traffic flow predictions differ in relation to sample size of a population, a number of prediction runs of Albatross under different settings of sampling fraction level are conducted. The fractions assumed across runs of the model are 25%, 50% and 100% for the internal population and 2% and 4% for the external population. These levels where combined in a total of four runs of the model. Table 1 shows the assumed setting for each run.
Table 1. Assumed sampling fraction levels

<table>
<thead>
<tr>
<th>Model run</th>
<th>Inside study area</th>
<th>Outside study area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Project 1</td>
<td>25%</td>
<td>2%</td>
</tr>
<tr>
<td>Project 2</td>
<td>50%</td>
<td>2%</td>
</tr>
<tr>
<td>Project 3</td>
<td>100%</td>
<td>2%</td>
</tr>
<tr>
<td>Project 4</td>
<td>100%</td>
<td>4%</td>
</tr>
</tbody>
</table>

### 4. Results

In the base year of the Albatross model, the year 2000, which is used for the simulations, the Netherlands has 15.9 million inhabitants of which 2.5 million live in the North-Holland study area. The simulated population only includes the adults in households; on that level the population sizes are 11 million (all of the Netherlands) and 1.7 million (study area). This means that for example for fractions of 4% (external area) and 100% (study area) the activity schedules of in total 2.1 million agents are simulated. For this analysis, a partly dynamic traffic simulation is assumed. That is to say, a static traffic assignment is carried out for each of the 15 time moments of the day. This shows dynamics in terms of how traffic loads on the network changes from hour to hour, however, without considering a continuous propagation of traffic through time. This set-up allows us to test simulation error under the condition of temporal disaggregation of traffic flows of a degree generally considered in dynamic traffic modeling. The OmniTrans software is used for the traffic assignment step.

![Graphical representation of predicted number of trips](image-url)
Summary results of predicted flows
Figure 2 represents the total number of trips (after scaling) for each time moment graphically. Since the sampling fractions have been taken into account, the expected values of the flows are the same across projects and, indeed, there seems to be little difference in the height of bars. Although differences between projects (sample sizes) are slightly bigger for 3 – 6 am compared to other times of day, the differences are mostly less than 1%. This indicates that prediction of traffic flows on this aggregated level is rather robust for choice of sample size in the range investigated.

Results at road segment level
Traffic assignment results in traffic loads for each of the 15 moments of the day. It is expected that the effect of sampling error on traffic load predictions is larger on times and places where flows are small and vice versa. Therefore, in the analysis conducted we distinguished between local roads and highways. 20 links are selected for analysis: 10 links on highway and 10 links on more local roads (see Table 2). The selected highway links are generally a part of major routes. As for local-road links, 10 municipalities at province North-Holland are chosen which vary in terms of population density. Listed from high to low population density, inner city of Amsterdam has the highest population density and Schagen has the lowest density. The highway links and the local road links are analyzed separately because these road types may behave differently, as said. Figures 3 and 4 graphically show the time-of-day profile of predicted traffic flows for an example of a highway link and an example of a local-road link, respectively. The variance across runs (projects) indicates sampling error, which, in the cases shown, appear to be larger for the local road than for the highway.

<table>
<thead>
<tr>
<th>Link Type</th>
<th>Link Number</th>
<th>Link Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highway</td>
<td>112269</td>
<td>A9</td>
</tr>
<tr>
<td></td>
<td>112235</td>
<td>A200</td>
</tr>
<tr>
<td></td>
<td>114315</td>
<td>A4</td>
</tr>
<tr>
<td></td>
<td>113401</td>
<td>A4</td>
</tr>
<tr>
<td></td>
<td>109863</td>
<td>A10</td>
</tr>
<tr>
<td></td>
<td>109823</td>
<td>A7</td>
</tr>
<tr>
<td></td>
<td>112443</td>
<td>A1</td>
</tr>
<tr>
<td></td>
<td>111856</td>
<td>A6</td>
</tr>
<tr>
<td></td>
<td>107326</td>
<td>A2</td>
</tr>
<tr>
<td></td>
<td>117453</td>
<td>A5</td>
</tr>
<tr>
<td>Local road</td>
<td>30869</td>
<td>Amsterdam</td>
</tr>
<tr>
<td></td>
<td>10224</td>
<td>Haarlem</td>
</tr>
<tr>
<td></td>
<td>12439</td>
<td>Zaanstad</td>
</tr>
<tr>
<td></td>
<td>11026</td>
<td>Haarlemmermeer</td>
</tr>
<tr>
<td></td>
<td>11595</td>
<td>Alkmaar</td>
</tr>
<tr>
<td></td>
<td>31785</td>
<td>Amstelveen</td>
</tr>
<tr>
<td></td>
<td>11764</td>
<td>Den Helder</td>
</tr>
<tr>
<td></td>
<td>11464</td>
<td>Aalsmeer</td>
</tr>
<tr>
<td></td>
<td>35260</td>
<td>Diemen</td>
</tr>
<tr>
<td></td>
<td>12387</td>
<td>Schagen</td>
</tr>
</tbody>
</table>
Figure 3. Predicted traffic flows across projects for an example local-road link

Figure 4. Predicted traffic flows across projects for an example highway link (of the A4)
We expect that the traffic flow predictions show more random variation when sample size is small and vice versa. We use an analysis of variance to address the following two questions: i) to what extent does sample size have an impact on predicted traffic patterns? And ii) Does sample size influence traffic flows on highways and local roads differently? To measure variance caused by simulation error we use the following procedure. First, for each link and each time moment, we calculate overall means ($\bar{x}_{it}$, where $i$ is link $t$ is time of day) of traffic loads across the four projects. These means represent best estimates of the true load as simulation error will cancel out when runs are merged. Error variance is then calculated for each project $k$ as the sum of squares of differences between obtained load and average load across the links. In formula:

$$ME_{tk} = \sqrt{\frac{\sum(x_{itk} - \bar{x}_{it})^2}{I}}$$  \hspace{1cm} (1)

where $x_{itk}$ is the predicted size of the traffic load on link $i$ at time moment $t$ in project run $k$, $\bar{x}_{it}$ is the estimate of the true value and $I$ is the total number of links. This measure indicates the average size of simulation error across the links. In addition, it is relevant to consider the relative size of error, that is, the size as a proportion of the mean traffic load. Hence, we define:

$$RME_{tk} = \frac{ME_{tk}}{\bar{x}_{tk}}$$  \hspace{1cm} (2)

where $\bar{x}_{tk}$ is the average across links. We calculate the measures $ME$ and $RME$ separately for local roads and highways (where $I = 10$ in both cases). Furthermore, in order to test statistical significance of differences in error variance between projects we calculate an overall measure of variance across time moments, as follows:

$$SS_k = \frac{\sum\sum(x_{itk} - \bar{x}_{it})^2}{I \cdot T - 1}$$  \hspace{1cm} (3)

where $T = 15$ is the number of time episodes distinguished and other symbols are defined as before. $I \cdot T - 1$ is number of degrees of freedom. This measure of variance ($SS$) allows us to test the statistical significance of differences in error between projects (sampling fraction sizes). The ratio of $SS$-values between any two projects has an F-distribution with ($I \cdot T - 1$) and ($I \cdot T - 1$) degrees of freedom.

Figures 5 and 6 show graphically the RME for highway links and local-road links, respectively. In each figure, the top graph shows the comparisons between runs (projects) that vary only in terms of sampling fraction size of the internal population (25, 50 and 100% in projects 1, 2 and 3) and the bottom graph relates to a comparison of different sampling fraction size of the external population (2 and 4% in projects 3 and 4). First, turning to highways (Figure 5), we see that relative error is large in the early morning episode (3 – 6 am) when the travel demand is small. The morning peak (episodes 6 – 8 am and 8 – 9 am) is visible as a sharp decline in relative error. After the morning peak the error increases again and from that moment on shows a steady decline as time progresses. Comparing the graphs
between projects that differ in internal sample size we see an overall trend of a decrease in error. The decrease seems somewhat more pronounced in going from 25 and 50% (compare projects 1 and 2) than in going from 50 to 100% (compare projects 2 and 3). On the other hand, the variation in external sample size (2 versus 4%) does not show a clear effect on error.

Next turning to local roads (Figure 6), we similarly see that error is large for the early episode of the day (3 – 6 am) when there is hardly any traffic. The morning peak shows a modest decrease in error as well. However, for the remaining of the day there does not seem to be a decline in error with passage of time as we saw in case of highways. Comparing the projects that differ in internal sample size (top graph), we see a decreasing trend when going from 25 to 50%, but hardly any further decrease in error when going from 50 to 100%. Comparing the projects that differ in external sample size (bottom graph), there does not seem to be a clear impact of sample size (2 or 4%). The highways and local roads differ in terms of the relative size of the error. In case of highways, the error is roughly in the range of 5 to 10% and in case of local roads in the range of 10 to 20% (the early morning episode not included).

Figure 5. Relative simulation error: highway links
Figure 6. Relative simulation error: local-road links

Figure 7. Normal Q-Q plot of error-variance measure
Table 3 shows the results of the analysis of error variance (the $SS$ measure) and Table 4 represents the results of the corresponding significance tests. An F-test requires that $SS$ is normally distributed. Normality of the data is checked by drawing a so-called normal Q-Q plot. Figure 7 displays the result of such a normality test. The straight line represents the data when it is perfectly normally distributed and the line of dots is the observed values from the data. Thus, the closer the plots are to the 45-degree reference line, the more likely it is that the data are normally distributed. Although the plot shows the distribution deviates somewhat from normality at the low end, it overlaps the reference line largely. Therefore, it can be concluded that the data is close to normal implying that the F-test can be applied to this data.

### Table 3. Mean error variances ($SS$)

<table>
<thead>
<tr>
<th>Link Type</th>
<th>Project</th>
<th>Sampling fraction (external between brackets)</th>
<th>Mean error variance ($SS$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highway</td>
<td>1</td>
<td>25% (2%)</td>
<td>65856.4</td>
</tr>
<tr>
<td>Highway</td>
<td>2</td>
<td>50% (2%)</td>
<td>53858.2</td>
</tr>
<tr>
<td>Highway</td>
<td>3</td>
<td>100% (2%)</td>
<td>38389.1</td>
</tr>
<tr>
<td>Highway</td>
<td>4</td>
<td>100% (4%)</td>
<td>42788.2</td>
</tr>
<tr>
<td>Local road</td>
<td>1</td>
<td>25% (2%)</td>
<td>3693.9</td>
</tr>
<tr>
<td>Local road</td>
<td>2</td>
<td>50% (2%)</td>
<td>2156.4</td>
</tr>
<tr>
<td>Local road</td>
<td>3</td>
<td>100% (2%)</td>
<td>2874.0</td>
</tr>
<tr>
<td>Local road</td>
<td>4</td>
<td>100% (4%)</td>
<td>1605.3</td>
</tr>
</tbody>
</table>

First we consider highways (top section of Table 4). The decrease in error when sampling fraction is increased from 25 to 50% is not significant ($F = 1.22$, $p = 0.11$), but the decrease is significant when the sampling fraction is increased from 25 to 100% ($F = 1.72$, $p = 0.001$) or from 50 to 100% ($F = 1.40$, $p = 0.02$). This suggests that in case of highways the internal sampling fraction should be larger than 50% and possibly could be smaller than 100%. In terms of the external sampling fraction, we see that there is no significant difference in error rate when the sampling fraction is increased from 2 to 4% (the error is even larger in the 4% case, but the difference is not significant). This suggests that in case of highways an external sampling fraction as small as 2% already suffices.

### Table 4. Results of F-tests of difference in error variance

<table>
<thead>
<tr>
<th>Link Type</th>
<th>Sampling fraction (external between brackets)</th>
<th>Test Statistic</th>
<th>p-value</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highways</td>
<td>25/50% (2/2%)</td>
<td>$F_{12} = 1.22$</td>
<td>0.110</td>
<td>Not significant</td>
</tr>
<tr>
<td>Highways</td>
<td>25/100% (2/2%)</td>
<td>$F_{12} = 1.72$</td>
<td>0.001</td>
<td>Very significant</td>
</tr>
<tr>
<td>Highways</td>
<td>50/100% (2/2%)</td>
<td>$F_{23} = 1.40$</td>
<td>0.020</td>
<td>Significant</td>
</tr>
<tr>
<td>Highways</td>
<td>100/100% (2/4%)</td>
<td>$F_{34} = 0.90$</td>
<td>0.746</td>
<td>Not significant</td>
</tr>
<tr>
<td>Local roads</td>
<td>25/50% (2/2%)</td>
<td>$F_{12} = 1.71$</td>
<td>0.001</td>
<td>Very significant</td>
</tr>
<tr>
<td>Local roads</td>
<td>25/100% (2/2%)</td>
<td>$F_{12} = 1.29$</td>
<td>0.063</td>
<td>Not quite significant</td>
</tr>
<tr>
<td>Local roads</td>
<td>50/100% (2/2%)</td>
<td>$F_{23} = 0.75$</td>
<td>0.960</td>
<td>Not significant</td>
</tr>
<tr>
<td>Local roads</td>
<td>100/100% (2/4%)</td>
<td>$F_{34} = 1.79$</td>
<td>0.000</td>
<td>Very significant</td>
</tr>
</tbody>
</table>
In case of local roads (bottom section of Table 4), the pattern is different. Here we see in case of internal sample, that the decrease in error is significant when the sampling fraction increases from 25 to 50%, whereas a further increase does not give a significant reduction of error (there is even an increase in error when the sample size is increased from 50 to 100%, but the difference is not significant). This suggests that in case of local roads the internal sampling fraction should be larger than 25% but can be smaller than 50%. As for the external sampling fraction, the decrease in error is significant when the fraction increases from 2 to 4% suggesting that for local roads a fraction of 2% for the outside area is not sufficient.

In sum, the results suggest that highways compared to local roads require different sample size. Surprisingly, for highways the sample fraction should be higher in the internal area and can be lower in the external area. A possible explanation is that traffic from outside the area tends to be largely focused on highways so that a small sampling fraction of the external population is already sufficient. On the hand, local traffic will be more concentrated on local roads so that a smaller internal sampling fraction already suffices to obtain stability for local roads. At the same time, external traffic will be more distributed across local roads (either at origin or destination) so that a larger sampling fraction from the external population is required to obtain stability in predictions for local roads. Of course, the highest demand is what counts so that we can conclude that local roads determine the external sampling fraction size and highways the internal sampling fraction size.

5. Conclusions and discussion

In this study we considered the coupling of dynamic traffic modeling and activity-based travel demand modeling and addressed the question what the impact of simulation error of the activity-based model is on the reliability of traffic-flow predictions. This question is relevant since dynamic traffic modeling compared to static traffic modeling implies a higher degree of disaggregation of travel demand predictions to provide the time dimension in the distribution of trips in the study area. Since simulation error is a function of size of the synthetic population (or number of runs of the model) used in the simulation, we addressed this question under varying conditions of sampling fraction and distinguished between the population inside the study area and the population outside the study area (of the traffic model).

The results of an analysis of error variance indicates that, as expected, (relative) error is larger at times and places when the size of predicted traffic flows is smaller. This certainly is a convenient finding as the practical significance of accuracy (reliability) of predictions increases with the size of traffic loads of roads (relative to the capacity) given the fact that an important objective of traffic modeling is to identify congestion problems. The results further suggest that local roads and highways behave differently. Local roads appear to be more sensitive to the sampling fraction of the external population, whereas highways show more sensitivity to the sampling fraction of the internal population. This means that to obtain sufficient reliability of predictions of (dynamic) traffic flows the internal sampling fraction is the bottleneck for highways and the external sampling fraction is the bottleneck for local roads. Thus, if prediction reliability is equally critical for local roads and highways the sampling fraction of the external population should be adapted to local-road conditions and the sampling fraction of the internal population should be adapted to highway conditions.
Obviously, it is hard to derive indications in terms of exact numbers of sample sizes. The case considered in the present study showed simulation error rates on the level of links at specific times of the day ranging from 3 to 8% for highways and from 5 to 15% for local roads when 100% of the internal population and 2% of the external population is simulated (1.8 million agents inside and 0.2 million agents outside the study area). Although for peak hours, the lower ends of these ranges will hold, the error rates are still substantial and certainly can make a difference in predictions of where and when congestion will occur on the network. This suggests that for obtaining sufficient reliability in practice a 100% internal sampling fraction is not sufficient for highways and a 2% external fraction is not sufficient for local roads. Since not more than 100% of a population can be synthesized, this means that multiple runs of the travel demand model are required (which is in fact a multiple of the population) in cases comparable to the case considered in the present study. Needless to say that this state of affairs should increase the motivation to develop better (activity-based) travel demand models in terms of size of error terms.

Several issues remain for future research. First, the analysis as conducted in the present study could be refined by using a finer classification of road types. Presently, we distinguished between local roads and highways where local roads constitute a rest category that could be further broken down in size categories. Such a refinement would give better insights in bottlenecks regarding the prediction of local traffic. Second, the present study could be extended to consider also the impacts of simulation error on travel-time or travel-speed predictions. This would yield more information about the practical significance of certain levels of simulation error when the purpose of the model is to identify congestion problems. Third, the analysis could be refined in terms of the specification of the model system. In the present study, we considered assignment of traffic for different time periods of the day where the temporal resolution of trip flows matches the demands of dynamic traffic modeling but where the propagation of traffic through (continuous) time was not taken into account. Using a full-fledged dynamic traffic model could lead to a further refinement of the analysis.

References

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Methods and application to a Dutch urban area, Environmental Impact Assessment Review, 29, 179 – 185.


